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The Role of Information in Agricultural Technology Adoption: Experimental Evidence from Rice Farmers in Uganda

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Contents

Tables

Figures

ABSTRACT

Optimal decision making among the poor is often hampered by a lack of critical pieces of information, false beliefs or wrong perceptions. This paper investigates the role of information deficiencies in the decision to use modern inputs and adopt recommended agronomic practices among rice farmers in Uganda. Using field experiments, we tested whether the provision of technical information concerning the existence and use of modern inputs and practices affects awareness and adoption of these technologies as well as farm production. In addition, we tested whether providing information aimed at changing the perception of returns on such intensification investments leads to different outcomes. In both experiments, the treatments took the form of short agricultural extension information videos shown to individual farmers using tablet computers. Although results show that the videos did seem to increase the awareness and influence the beliefs of rice farmers to some extent, practices and production generally seemed unaffected. Finally, the paper provides some clues as to why we find little impact on outcomes.

Keywords: agricultural extension services, information, ICT, rice, Uganda

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1 Introduction

There is substantial heterogeneity in farm household-level agricultural technology adoption in developing countries. The fact that at least some farm households seem to use certain modern inputs and cultivate according to recommended practices suggests that, overall, such intensification investments are profitable (Jack 2013). At the same time, many households continue to use traditional farming methods with few or no modern inputs. This apparent discrepancy may indicate the existence of market inefficiencies and transaction costs that drive a wedge between the costs and the benefits of intensification at the household level. An emerging body of literature uses field experiments to investigate the relative importance of these inefficiencies (de Janvry, Sadoulet, and Suri 2017). For example, Karlan and others (2014) compare the role of credit market inefficiencies and risk market inefficiencies in agricultural input expenditure in Ghana. Ali, Deininger, and Goldstein (2014) looked at how land market failures impact agricultural investment and land conservation techniques in Rwanda.

One particularly important inefficiency that emerges from this literature is related to information flows. Optimal decision making among the poor is often hampered by a lack of critical pieces of information or by erroneous beliefs (Banerjee and Duflo 2012). Technologies that are profitable will not be taken up without information about their existence, use, and profitability, especially when the technologies are new, are technically complicated, or require precise implementation (Jack 2013). Due to its public, nonrival nature, information is undersupplied by the private sector, so governments across the developing world have started providing extension information services on a large scale, albeit with mixed success. Although some studies have reported positive impacts of extension services, these effects are far from general, with cost-effectiveness, scalability, and accountability frequently cited as issues (Anderson and Feder 2007). More recently, information and communication technologies (ICT) has been advanced as a promising way to strengthen agricultural extension services (Aker 2011).

This paper reports on a study designed to investigate the impact of agricultural information provision on technology adoption among a sample of rice farmers in eastern Uganda. The information was provided in the form of short videos shown to individual rice farmers on Android tablet computers. The study targeted two different types of information deficiencies: First, farmers may simply lack technical knowledge. That is, they may not be aware of the existence of a particular improved input or practice, or they may not have knowledge on how to use or implement it correctly. Second, farmers may have insufficient information to assess the profitability of an input or technology. They may be uncertain about fixed and variable costs related to the investment, about the level and variability of the stream of future returns, and about the time frame. To investigate the importance of these two types of information inefficiencies empirically, we developed two corresponding interventions that targeted these information gaps among random subsets of rice farmers.

The study followed a crossed treatment design, wherein half of the farmers received the first intervention which targeted knowledge gaps on existence and use, and half received the second intervention, which informed them about the likely returns on intensification investments. Moreover, the experiment was designed such that half of the farmers who received the first intervention also received the second intervention, with a quarter of the sample receiving no treatment at all. Such designs require fewer observations than parallel designs and allow for the investigation of interaction effects between the two interventions (Montgomery, Peters, and Little 2003). In addition, to increase statistical power, instead of simple randomization, we used an ex ante matching procedure whereby farmers who were similar along a range of characteristics were matched into groups of four prior to randomization (Bruhn and McKenzie 2009).

The main outcome of interest is the extent of crop intensification investments among rice farmers, including the use of modern inputs such as inorganic fertilizer. We are also interested in the adoption of modern techniques and recommended practices such as optimal water management and correct timing of transplanting. Further down the causal chain, we also want to test whether technology adoption results in increased rice production and yields.

To investigate the causal chain, we will test whether the videos affected awareness of modern inputs and improved agronomic practices, as well as whether they led to a change in the perceived profitability of intensification investments. Some researchers have found evidence that videos featuring successful farmers affect aspirations and forward-looking behavior (Bernard et al. 2015), in turn resulting in differential technology adoption (Mekonnen and Gerber (2015)). Therefore, it may be that the videos in our study affected outcomes through influencing attitudes and perceptions without directly altering knowledge related to technologies or expected returns. We thus also investigate whether the videos affected a range of noncognitive personality traits, such as aspirations and locus of control.[1]

We find that providing technical information through short video extension messages improved farmers' awareness about optimal timing of transplanting and the use of crop residue for soil nutrient conservation, but not about proper water management. We do not find significant differences in perceived returns on fertilizer use, proper water management, and optimal timing between those who viewed the video about the returns on intensification and those who did not. Neither the intervention that focused on technical knowledge nor the one that aimed to sensitize farmers on returns seemed to affect practices such as fertilizer use or timely transplanting. Outcomes further down the causal chain, such as quantities of rice produced and yields, also seemed to be equal across treatment and control groups for both interventions. We find some indication that viewing the videos reduced external locus of control. We provide reasons why, despite the finding that the technology video changed awareness, this seems not to have translated into significant changes in behavior and outcomes.

The remainder of this article is organized as follows: The next section outlines the main research questions, provides the rationale behind the hypotheses to be tested, and situates the study in the broader literature. Section 3 presents the research method used to answer the research questions, starting with the research design and how the treatments were assigned, followed by a detailed description of the interventions. It also explains which specifications we will estimate to identify the causal effects of the interventions. section 4 presents the data and provides some descriptive statistics. Section 5 discusses the results, starting with an analysis of the impact of showing the videos on awareness of modern technologies and perceived returns. It then looks at the effect of providing information on the actual adoption of technology and recommended practices, and investigates whether the information interventions also altered outcomes such as rice production, area planted, and yields. Finally, the section assesses whether viewing the videos altered beliefs and attitudes related to rice farming. Section 6 provides plausible explanations for the many null results, and Section 7 concludes.

[1] *Locus of control* refers to an individual's belief about how much control he or she has over what happens to him or her in life. For example, people who tend to believe that events are due to chance and their actions have little impact have an external locus of control. People who believe that they can influence events and turn things to their advantage have an internal locus of control.

2 Research Questions and Hypotheses

If farmers do not know about the existence, use, or profitability of a certain improved input or technology, it is unlikely that they will adopt it. Therefore, most research on the role of information as a catalyst for technology adoption focuses on how farmers acquire such knowledge. Research has identified different ways in which farmers learn about new agricultural technologies. Governments and nongovernmental organizations may provide targeted extension services, such as farmer field schools, demonstration plots, or direct one-on-one visits to farmers. Farmers also learn from the private sector, such as from agrodealers who promote the products they sell. Often, outgrower programs, in which smallholder farmers enter into contracts with agroprocessors, include important training components. Farmers also seem to benefit from peer learning from neighbors and within social networks (Conley and Udry 2010; Bandiera and Rasul 2006). Finally, farmers also learn from experimenting on their own plots.

In most research on learning about agricultural technology adoption, no explicit difference is made between, on the one hand, knowledge about the existence and use of inputs and technologies and, on the other hand, knowledge about the expected returns on the use of such inputs and technologies. However, these two types of information may substantially differ in characteristics: Technical information can be thought of as having a largely public, nonrival character. Knowledge about the existence and use of modern inputs and technology is easily observed by fellow farmers and difficult to hide. Information about profitability seems much more idiosyncratic. Such information is much less easy to observe and easier to hide. In poorly integrated and shallow markets, such information may constitute a first-mover advantage, providing an incentive to keep the information private. From a policy perspective, some types of agricultural extension and some of the learning channels through which agricultural information is obtained may be more or less suited to transfer a particular type of knowledge. Therefore, in this research, we differentiate between these two types of information inefficiencies.

In a first hypothesis, we postulate that farmers lack technical knowledge, which constrains them from using modern agricultural inputs and technologies. Therefore, providing farmers with this information should increase agricultural technology adoption and subsequent yields. We will label the first type of information deficiency as the technological information (TI) constraint. To quantify the importance of this constraint, we designed a simple intervention to relax it. Specifically, we showed simple extension video messages to make farmers aware of existing inputs, technologies, and best practices, as well as how to use or implement them. Because it has been argued that ICT may provide a cost-effective way to address these information-related barriers to technology adoption, we showed the videos to individual farmers using Android tablet computers (Aker 2011). Similar information interventions using ICT have been promising and include the Grameen Foundation's use of smartphones in Uganda to provide extension information through community knowledge workers (Van Campenhout 2017) and a mobile phone based technology that allowed farmers to call a hotline and ask questions to agricultural scientists and extension workers (Cole and Fernando 2012).

In a second hypothesis, we presume that farmers refrain from adopting a particular input or technology because they lack knowledge about its profitability or return on investment. Investments in agricultural inputs or technologies requires the farmer to compare costs today wiht and uncertain future stream income. However, farmers may not have precise information about the fixed and variable costs involved, about the level and variability of the future stream of income, or about the time frame of both cost and income. Thus, they base their decision to invest on *perceived* return, which may substantially differ from actual return. This second type of information constraint will be referred to as the return-on-investment information (RI) constraint. To assess the importance of this particular information constraint, we developed a second information treatment similar to the TI intervention, again taking the form of a short video. This video took farmers through the calculations of returns on different rice crop intensification investment options. For instance, ti showed the farmer what it would cost to apply fertilizer to his or her field and what the expected return would be. In addition, this treatment also underscored the importance of taking a longer-run perspective, whereby costs are incurred now to increase returns in the future. Information treatments have been found to be effective in many other settings where perceptions are biased. For instance, Roth, Grigorieff, and Ubfal (2016) found that biased beliefs about the number of immigrants in a country can be reduced through simple information treatments. Jensen (2010) found perceived returns on education to be much lower than measured returns among students in the Dominican Republic; providing information about the correct returns significantly increased investment in schooling. In a similar study, Nguyen (2008) found that providing information about the returns on schooling, either through statistics or role models, increased schooling outcomes when actual returns were underestimated in Madagascar.

In both hypotheses, the core research questions relate to the role of the particular information deficit. The fact that this information is transferred using a video on a mobile device is of secondary importance. However, one may argue that merely showing a video to a farmer may affect the behavior of the farmer. Therefore, we need to account for the effect that comes from merely being shown a video, which can be done by including a placebo video. For instance, Bernard and colleagues (2015) used music videos as a placebo in their study of the potential of targeted exposure to role models through video to induce behavioral change in Ethiopia. However, in our case, with rather specific information in each video, showing a completely unrelated video such as a music video may be unsatisfactory. One could still argue that any observed effect may come from being shown a video containing any information on rice farming instead of from the actual information that is provided in the treatments. Therefore, we decided to produce a placebo video that resembled the treatments as closely as possible. The placebo video provided information on technical aspects related to postharvest handling of rice and its expected returns.[2] Although we chose the topic of the video such that it was unlikely to affect outcomes that are of interest in this study, such as adoption and yields, such effects cannot be entirely excluded.[3] We therefore decided to administer the placebo treatment to all participants, regardless of treatment assignment.

A clear distinction between technical information and information about profitability can help us understand the heterogeneity in the effectiveness of various learning channels. For instance, because social networks have been found to affect technology adoption, some researchers have started to investigate how these networks can be leveraged to make agricultural extension services more effective. Distinguishing between technical information and information about profitability helps us interpret recent findings such as those of Cai, De Janvry, and Sadoulet (2015), who found that social networks

[2]This video also provided useful information to participants, reducing the ethical objection to working with a control group that does not benefit from the study.

[3]For instance, farmers in the control group who get information on postharvest handling before the start of the growing season may anticipate higher prices due to a quality premium when they end up selling part of the rice after harvest. These expected higher prices may prompt the farmers to reevaluate the use of certain modern technologies, which may also affect yields.

are effective in disseminating only public information (such as information obtained at a training), but not more private information, such as actual adoption decisions. Such a distinction also helps explain why information on returns specific to the individual or household is more effective than general information (Jalan and Somanathan 2008). Finding out which of the two types of information deficiencies dominates may also help in predicting what learning channels are most effective: For instance, demonstration plots are likely to increase technical knowledge but may be less effective in reducing knowledge gaps related to the return on investment. On the other hand, farmers may learn more about the profitability of a particular technology through their interactions with agro-input dealers or their participation in outgrower programs.

3 Research Methods

This section presents the research design and tools that were used in the field. It also elaborates on treatment assignment and presents the empirical specifications for testing. To reduce bias related to the choice of outcome measures and model selection, we registered a pre-analysis plan at the American Economics Association's randomized controlled trials registry.[4] In addition, to guarantee full transparency and facilitate replication of the study, the project is under revision control and publicly available[5].

3.1 Experimental Design

To test the hypotheses set out in the previous section, we used a simple field experiment. We showed a random subset of a sample of rice farmers a video that provided a particular piece of information. To assess the effectiveness of this information, we compared these farmers' outcomes in terms of knowledge, attitudes, technology adoption, production, and yields with the outcomes of farmers who were not shown that particular video. The experiment takes the form of a two by two full factorial design, in which each of the two factors corresponds to a different hypothesis. The first factor tests the hypothesis that low technology adoption mainly emanates from limited

[4] www.socialscienceregistry.org/trials/1312
[5] www.bitbucket.org/bjvca/ricerct/overview

Figure 1: Experimental design

		Technical knowledge factor	
		Control	TI treatment
Returns on investment knowledge factor	Control	55	55
	RI Treatment	55	55

Source: Authors
Note: RI = return-on-investment information intervention;
TI = technical information intervention.

technical knowledge. This factor has two levels, one corresponding to being shown the TI video and the consisting of the control, in which the TI video was not shown. The second factor tests the hypothesis that farmers are constrained by lack of information related to the return on intensification investments. This factor also has two levels, one consisting of the RI treatment and the other the control, in which the RI video was not shown. Figure 1 summarizes the experimental design. Power calculations, which can be found in the pre-analysis plan, suggested the need for 55 observations in each treatment cell, leading to a total of 220 observations.

The factorial design allows us to test different hypotheses with a smaller sample size.[6] In our design, half of the sample received the TI treatment and the other half did not. Similarly, half of the sample received the RI treatment and the other half did not. However, these two factors overlap in that half of the individuals assigned to the TI treatment also received the RI treatment, with the result that one-fourth of the sample received neither the TI nor the

[6] As compared with the standard parallel design, in which mutually exclusive groups for each treatment are compared with a control.

RI treatment.[7] The entire sample is used to test the TI hypothesis because all subjects who received the TI treatment (half of whom also received the RI treatment) can be compared with all subjects who did not receive the TI treatment (half of whom received the RI treatment). Similarly, to test the hypothesis that subjects are constrained by a lack of knowledge of the benefits related to intensification, all subjects who received the RI treatment (half of whom also received the TI treatment) can be compared with all subjects who did not receive the RI treatment (half of whom received the TI treatment). Because such a factorial design recycles subjects while keeping factors mutually orthogonal to each other, it makes very efficient use of experimental subjects (Collins, Dziak, and Li 2009). An additional advantage of factorial designs is that they allow for the estimation of interaction effects between different factors.[8]

3.2 Treatment Assignment

Instead of a simple randomization that would allocate farmers randomly to each of the four treatment combinations (Control, TI, RI, and TI + RI), we used an ex-ante matching procedure, matching farmers that were similar along a range of characteristics into groups prior to randomization.[9] Such a procedure guarantees that farmers whho are similar in some characteristics, for instance income, are allocated to different treatment groups. In this way, it reduces the chance that a disproportionate number of high-income farmers are allocated to a particular treatment, which would make it difficult to differentiate between the treatment effect and a potential income effect. Especially in small samples, randomization procedures based on matching can significantly improve the statistical power of hypothesis tests (Bruhn and McKenzie 2009). King and others (2007) pointed out an additional advantage: if a unit drops out of the survey, its paired observations can also

[7] This quarter of the sample received only the placebo treatment.

[8] Our study was not designed to have sufficient statistical power to detect interaction effects. Therefore, they are not the main focus in this study.

[9] The size of the groups is determined by the number of treatment combinations. In a simple treatment-versus-control experiment, there are only two experimental conditions (Control, Treatment) and the "groups" consist of two experimental units. This is the more common type of matching and is generally known as pairwise matching (Greevy et al. 2004). Our factorial design has four treatment combinations (Control, TI, RI, and TI + RI), so we have groups of four experimental units. Instead of *pairs*, we will thus refer to these groups as *quadruplets*.

be dropped without compromising overall balance.

We used data from a baseline survey to match farmers into groups of four, based on proximity along a range of observed characteristics. To do so, we developed an algorithm that minimizes euclidean distance between farmers on a set of covariates. The algorithm starts by randomly selecting a farmer from the sample of rice farmers that need to be matched. It then calculates euclidean distance as the square root of the sum of squared standardized differences of the measures for the various characteristics between this farmer and all the other farmers who need to be matched. On the basis of this criterion, the three most similar farmers in the sample are identified. The resulting four farmers are then allocated a unique number, and the quadruplet is removed from the sample of unmatched farmers and added to the sample of matched farmers. This procedure is repeated until the desired sample size is obtained.

We matched on the following characteristics: household size; age and gender of the household head; the logarithm of rice productivity, defined as kilograms harvested per hectare; the area in hectares of rice grown; the logarithm of consumption per capita; the distance in kilometers to the nearest agricultural input provider; access to credit; and access to agricultural extension. We also maximized the physical distance between farmers within each quadruplet, based on Global Positioning Systems (GPS) coordinates to reduce potential spillover effects.[10] All characteristics received an equal weight in the objective function.

3.3 Treatments

The treatments used to test the hypotheses outlined in the previous section consisted of information treatments in the form of short (about five-minute) videos that were shown to individual farmers, either in their homes or in the field.[11] A total of three videos were produced: one video for the TI treatment, one video for the RI treatment, and one placebo video. To de-

[10]Maximizing distance within each quadruplet will not completely eliminate spillover effects because two farmers from different quadruplets may be located close to each other. However, we do expect maximizing physical distance within each quadruplet to reduce any spillover effects that are more likely between people who are more similar with respect to the characteristics that were included in the matching procedure.

[11]The videos were shown in July and August 2016 because the study targeted the second rice-growing season in 2016.

termine the content of the videos, we held extensive interviews with farmers and experts on rice growing in the region. From these interviews and some additional analysis of the baseline data of our study population, we distilled the most important inputs and recommended methods in rice growing:[12] water management, soil nutrient management, and adhering strictly to recommended timing. These three key "technologies" appeared in both treatments. However, the TI treatment video focused on raising awareness of these three technologies and showing how they should be implemented. The RI video, on the other hand, emphasized the expected returns on these three technologies. The placebo video addressed on postharvest handling, such as proper drying techniques, and provided a mix of both technical information and information related to the expected profitability of proper storage and handling. All videos were produced in English and also in the main local languages used by the rice farmers who participated in the study (Lusoga, Japadola and Lunyole).

The TI video starts with the introduction of "John", who is presented as a fellow rice farmer. A narrator says John will show how to grow rice using recommended practices and inputs, which relate to good water management, proper timing, and optimal fertilizer use. The video points out that it is important to plan well ahead and start preparing rice fields before sowing. It shows how to construct contour bunds to keep water in the garden, suggests that fields should be moist for easier plowing, and advises submerging the field after plowing. The nursery should then be started, sown at a rate of 15 kg of clean seed per acre. The video then shows how the rice field should be leveled and submerged. It advises farmers, after 14 days, to reduce water levels to at most 1 inch and apply 25 kg per acre of nitrogen, phosphorus and potassium (NPK) or diammonium phosphate (DAP) while transplanting. John then demonstrates optimal distance and depth for transplanting. Next, the video shows John increasing water levels to 2 inches 14 days after transplanting, and broadcasting 25 kg per acre of urea inorganic fertilizer. The water, now mixed with the fertilizer, should remain in the field for 14 days, the video advises. Five weeks after the first urea application, farmers should apply ureas a second time, again at a rate of 25 kg per acre. Finally, one week before harvest, water should be gradually reduced. The video ends by summarizing the most important steps in rice rowing, underlining the im-

[12] "Most important" means that (a) the technology or practice offers substantial scope to increase productivity, and (b) few farmers are already using it.

portance of adhering to timing, water management, and fertilizer quantities.

The RI video introduces both "John" and "Richard". John, who uses recommended practices and modern inputs, is shown to harvest much more than Richard, who does not. John, the video says, sees rice growing as a business and invests now to increase yields in the future, whereas Richard is seen drinking beers with his friends in a local bar. The video then becomes more specific, mentioning that John transplanted seedlings on time, but Richard was late, resulting in John's harvesting 3.5 bags of paddy more on each acre than Richard. Similarly, the narrator points out that proper water management has the potential to increase yields by 3.0 bags per acre and inorganic fertilizer use can increase yields by 3.5 bags per acre. The presentation then turns to the idea of investing now for higher future returns. In a split screen, John is seen buying fertilizer for 40,000 Ugandan shillings (USh) while Richard spends this money buying beers for his friends in the bar. John's investment, the narrator explains, resulted in an extra bag of rice per acre, each of which can be sold for USh 180,000. John, the narrator concludes, can now also buy a few beers for his friends, but he also has money left to pay schoolfees. The video makes a similar argument about time invested in preparing the field, pointing out that many investments have returns that go beyond just one season. Field preparation, such as leveling and bund construction, prevents runoff of fertile topsoil, increasing yields in many years to come. Finally, the narrator explains that one can start small but grow over time by reinvesting time and money in inputs and practices. The video ends by summarizing the main points: the expected returns on fertilizer use and proper time and water management, the benefits of investing time and money now to increase yields in the future, and the benefits of taking a longer-run perspective beyond just one season.

Finally, the placebo intervention consisted of a short video showing recommended postharvest handling practices of rice and the expected returns on these practices. This video also starts by introducing "John", showing him drying paddy on a tarpaulin, a practice that has the potential to increase the market price of rice form USh 170,000 to USh 180,000 per bag. Paddy, the video continues, should be spread out at a thickness of about 2 inches, or 5 centimeters, and stirred every 30 minutes to allow equal exposure to sun. Doing so can increase the price per bag from USh 170,000 to USh 190,000. Drying paddy for the ideal period of three to four days, exposing it to direct sunlight for not more than three hours each day, can increase the seller's price for a bag of rice to USh 180,000. Finally, the video advises farmers not to sell rice immediately after the harvest but rather to wait three months, which can increase the price again from USh 170,000 per bag to USh 180,000. The video closes by repeating the main points.

The use of video to transfer information has some advantages over other ways to transfer information. First, the use of a prerecorded video results in a standardized treatment for all subjects in the same treatment group. Although one may argue that providing the information through human mediators may prove more effective because the trainer may adapt the message to, for example the education level of the recipient, this approach may also lead to subtle differences in the message given, making it difficult to differentiate the effect of the information from that of these small adaptations of the message. In addition, the videos were administered at the individual level. Again, one may argue that providing the information at a more aggregate level, such as to cooperatives, may be more cost-effective. However, it may be difficult to control group dynamics and hence, providing information to groups may again lead to heterogeneous treatments.

Compared to alternative modes of information delivery, video may also reduce spillover effects. For instance, providing posters or brochures that explain the use and profitability of fertilizer and pesticides may be more effective because it allows farmers to keep these materials and look back at them at different points in time. The video was shown only once, and farmers may forget some of the recommendations over time. However, print material can more easily be passed on to neighbors and relatives, potentially contaminating other treatment or control groups. Illiterate farmers also are likely to benefit more from videos than from written material (Nguyen 2008). Finally, we also chose to provide a relatively hands-off information treatment (instead of, for instance, providing inputs), because we wanted to evaluate an intervention that is cheap and relatively easy to bring to scale.

The videos were screened on Samsung Galaxy Tab 2 tablet computers. We developed an Open Data Kit (ODK) application with identification data and treatment assignment preloaded so that the correct video(s) for the respective treatment groups were automatically cued without the intervention of the enumerator. The ODK application also included a range of questions on viewing conditions and a series of questions designed to measure changes in knowledge, which farmers were asked immediately after the videos were shown. Farmers were offered a bar of soap as a token of appreciation. Because this gift was small in value and unrelated to agriculture, we deemed it unlikely to affect the outcomes studied.

3.4 Inference

To test the effectiveness of the TI and RI videos, we compare outcomes between treatment and control groups after the treatment. We run three different specifications, all of them assuming an additive structure in potential outcomes. We start by simply regressing the outcome variable (y_{ir}) of individual i in treatment group r on a constant and an indicator dummy for the treatment group (T_r):

$$y_{ir} = \alpha + \beta T_r + \varepsilon_{ir} \tag{1}$$

In this equation, the coefficient estimate on the indicator dummy for the treatment, β_r, corresponds to the first estimate of the treatment effect, and ε is an error term. This specification basically amounts to a simple t-test of equality of means in the two groups and is sometimes advocated as the preferred way to analyze data from experiments (Athey and Imbens 2017).

Equation 1 does not account for the matched randomization outlined in the section on sampling, above. Not including controls for the quadruplets in the analysis is known to lead to overly conservative standard errors and a significant reduction in power (Bruhn and McKenzie 2009). Therefore, in a second specification, we include fixed effects for each matched quadruplets. In addition, in our factorial design, the orthogonal treatment is likely to increase the variance in the outcome. Hence, we can increase power by controlling for the other treatment (T_{-r}):

$$y_{ijr} = \alpha_j + \beta T_r + \gamma T_{-r} + \varepsilon_{ijr} \tag{2}$$

Here, separate fixed effects, α_j, are estimated for each quadruplet, $b_j = \left\{b_1, ..., b_{n/4}\right\}$.

Finally, it has become standard to control for the value of the dependent variable at baseline when analyzing data derived from experiments. Therefore, for outcome variables for which we also collected baseline data, such as rice yields, we rerun the model in Equation 2 but add a control for the baseline value of the outcome. In particular, we estimate

$$y_{ijr} = \alpha_j + \beta T_r + \gamma T_{-r} + \theta y^b_{ijr} + \varepsilon_{ijr} \tag{3}$$

where y^b_{ijr} represents the value of the dependent variable at baseline.

4 Data and Descriptive Statistics

The study was conducted among smallholder rice farmers in three districts (Tororo, Butaleja, and Bugiri) in eastern Uganda. The sampling area is located south of lake Kyoga, a large shallow lake. Large parts of the area can be irrigated using rainwater that runs from the slopes of Mount Elgon in the southeast to the lake though numerous small rivers and canals. Between June and August 2014, we collected detailed socioeconomic data from about 400 smallholder rice farmers. Analysis of these baseline data showed rice yields averaging about 2 MT/ha, and slightly higher if we restrict attention to the main rice-growing season (the second season of 2013). These yields represent a significant productivity gap when compared with potential yields obtained in research stations in the area (about 5 MT/ha). In addition, within the area, yields vary substantially, and the distribution is skewed to the right, with many farmers having lower-than-average yields and a few obtaining very high yields. For instance, although median yields were only about 1.7 MT/ha, the 10 percent of farmers with highest yields attained 3.6 MT/ha, suggesting ample room for intensification among rice farmers in the region. From the 400 farmers surveyed, we randomly selected 252 farmers to enroll in the field experiment on the role of information in rice intensification.[13] Each farmer was allocated to 1 of the 4 possible treatment combinations using the matching procedure described above, resulting in 63 farmers in each of the 4 treatment combinations.

We report descriptive statistics on a range of variables from the baseline survey in the first column of Table 1. To test orthogonality, we regressed each variable on a treatment indicator and a set of dummies for the matched quadruplets (Equation 2). The second column of Table 1 investigates the balance (that is, the difference in the average outcomes at baseline) between the group that will receive the video on existing intensification inputs and technologies (the TI treatment) and the group that will not receive the TI treatment. In a similar fashion, the third column compares average outcomes at baseline for farmers who will be exposed to the RI treatment and those who will not.

The results show that, on average, households involved in rice growing are large, consisting of more than seven members, considerably more than

[13] Although power calculations suggested we would need only about 220 observations, we decided to enroll 252.

Table 1: Orthogonality tests

	Mean	TI	RI
Household size	7.45	0.20	0.13
	(2.81)	(0.232)	(0.232)
Age of head	41.96	-1.96+	1.66
	(12.90)	(1.078)	(1.081)
Can read and write	0.59	-0.12*	0.04
	(0.49)	(0.055)	(0.056)
Total ha under cultivation	1.67	0.01	0.07
	(1.40)	(0.164)	(0.164)
Area of rice (ha)	0.85	0.05	0.02
	(0.58)	(0.050)	(0.050)
Log rice production	7.48	0.06	-0.02
	(0.71)	(0.057)	(0.057)
Log welfare per capita	7.67	0.02	0.03
	(0.47)	(0.039)	(0.039)
Use of fertilizer on rice	0.23	0.06	-0.02
	(0.42)	(0.049)	(0.049)
Has mobile phone	0.75	-0.02	-0.07
	(0.43)	(0.056)	(0.056)
Distance to nearest market	4.94	1.37*	-0.84
	(4.72)	(0.595)	(0.600)
Distance to input provider	6.27	-0.98+	-0.65
	(6.61)	(0.538)	(0.540)
Access to extension	0.15	0.01	0.02
	(0.35)	(0.022)	(0.022)
No. of obs.	252	252	252

Source: Authors

Notes: Standard errors in parantheses. RI = return-on-investment information intervention, TI = technical information intervention

+, *, and ** denote significance at the 10 percent, 5 percent, and 1 percent level

the national average of about five. The average appears to be the same irrespective of treatment group. The average age of the household head is about 42 years, but among the TI treatment group, it is almost 2 years lower. About 60 percent of our sample of rice farmers reported being able to read and write, but this proportion is about 12 percentage points lower in the TI treatment group. On average and balanced among the various treatment groups, these households cultivated about 1.67 hectares of land, of which about 0.85 hectares was used for rice farming. The average logarithm of rice produced was about 7.48, corresponding to about 1,772 kilograms. Welfare in the sample, as proxied by consumption per capita per day, stands on average at USh 2,143.[14] We further find that 23 percent of rice farmers used fertilizer on rice and 75 percent of farmers had a mobile phone, with no differences between the treatment groups. Average distance to the nearest market was estimated at about 5 kilometers, but it was significantly higher among farmers assigned to the TI treatment. Distance to the nearest input provider was more than 6 kilometers, with some imbalance for the TI experiment. Finally, only 15 percent of rice farmers reported having access to extension. In short, of the 24 orhtogonality tests, we find 2 to be significant at the 5 percent level and 2 at the 10 percent level, leading us to conclude that randomization was successful.

5 Results

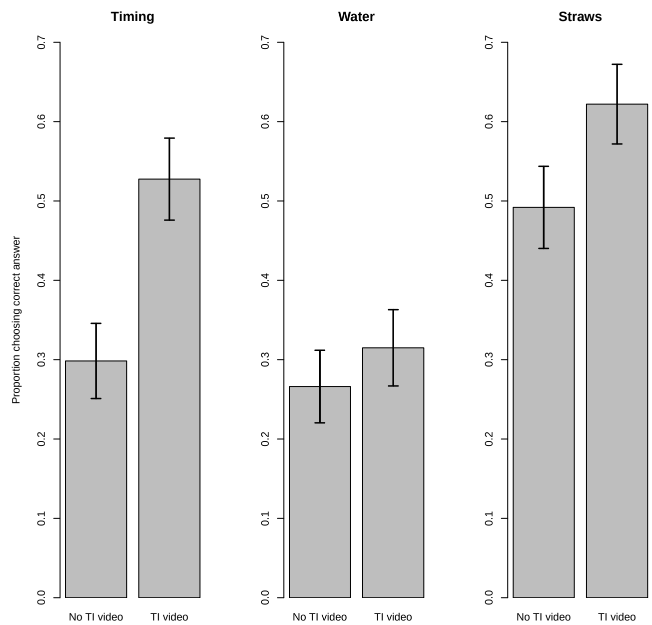
We now turn to outcomes. Although some outcomes related to knowledge were collected immediately after administration of the treatment, most of the other outcomes were measured about six months after the treatment. During these six months, farmers went though a full rice-growing cycle.

5.1 Impact on Awareness, Knowledge, and Perceptions

If farmers fail to intensify because they are unaware of the existence of yield-improving technologies or because they do not know how to use them, increasing technical knowledge may result in increased adoption and subsequent higher outcomes. This impact pathway implies that showing a video that explains what technologies exist and how to use them should increase

[14]This amount corresponds to about US$0.82 at the exchange rate of about USh 2,600 / US$1 at the time of the survey.

Figure 2: Technical knowledge after viewing technical information video



Source: Authors.
Note: TI = technical information.

knowledge about the featured technologies. To test this hypothesis, we asked farmers three multiple-choice questions immediately after they were shown the TI video. We then calculated the proportion of farmers who were able to pick the correct answers and compared the results between farmers who saw the TI video and those who did not. The questions concerned (1) the recommended time for transplanting, (2) knowledge about proper water management, and (3) what should be done with rice straw left in the field after harvesting. The results are presented in Figure 2.

The TI video effectively increased knowledge related to the timing of transplanting rice. The leftmost pair of bars in Figure 2 shows the results of the question on knowledge about the recommended time for transplanting. Transplanting should be done 14 days after sowing, and yields decrease rapidly when transplanting is delayed (Pasuquin, Lafarge, and Tubana, 2008). Agricultural experts in rice-growing areas in Uganda often blame low yields on late transplanting; therefore the TI video recommended early transplanting. Overall, we find that, when asked about the recommended time for transplanting, about 41 percent of farmers in our sample were able to indicate the correct answer (after 14 days) from among the alternatives (after 25 days; after 35 days; don't know). The barchart shows that farmers who were shown the TI video were more likely to pick the correct alternative: Among those shown the video, about 53 percent indicated the correct answer. Only 30 percent of farmers who were not shown the TI video indicated the correct answer (p-value that difference is significant < 0.001).

The middle pair of bars in Figure 2 shows results for knowledge about water management. In particular, we asked how water should be managed immediately after fertilizer application. Agricultural experts have pointed out that fertilizer often does not seem to work because of poor water management. They stress the importance of keeping water in the field, such that fertilizer does not run off with the water and become wasted. We also made this practice an important recommendation in the TI video. In our sample of rice farmers, only about 29 percent knew that water should be kept in the field after fertilizer application. Most thought water should be reduced gradually, and others thought it should be drained immediately after fertilizer application. The barchart shows that although the percentage of farmers who picked the correct choice on water management with fertilizer use was higher among those who received the TI treatment, the difference is not statistically significant (p-value $= 0.476$).

The rightmost pair of bars in Figure 2 shows the results on farmers' knowledge about what should be done with rice straws left in the field after harvesting. Farmers usually burn these straws, but it is recommended that the straws be spread out in the field to decompose, return plant nutrients to the soil, and reduce nutrient mining. This recommended practice was not explicitly featured in the video. We find that, overall, about 56 percent of farmers knew that spreading straw in the field is recommended. Somewhat surprising, we find that showing the TI video seemed to increase the proportion of farmers who picked the correct answer, even though this information did not feature explicitly in the video (p-value $= 0.052$). One explanation may be that being exposed to a video that focuses on the use of fertilizer induces farmers, when confronted with this question, to think about soil fertility and the benefits of leaving straws in the field. This explanation is consistent with results emerging from similar research among potato growers in Uganda that suggest farmers engage in a process of abstraction, actively applying insights gained in one context to a different context (Van Campenhout et al. 2017). These findings suggest that extension should be viewed as broader than just transferring technical knowledge and more as a learning experience. Put another way, it is better to broadly "educate" people than simply "train" them to perform particular tasks.

As mentioned above, farmers may be aware of a certain technology or practice but not of its expected benefits. They may perceive returns on the use of these technologies to be lower than what they actually are, leading them to refrain from intensification, as in Jensen's (2010) study on investment in education. If this were to be the case, we would expect to find adopters' perceived benefits of using the technology to be higher than those of nonadopters. We used a small thought experiment to elicit farmers' perceptions of the likely returns on the use of three core rice intensification strategies – fertilizer use, water management, and the use of good-quality seed: We asked farmers how many (100 kg) bags of paddy rice they would be able to produce on 1 acre when using fertilizer. We then asked these same farmers how much they thought they would get without fertilizer. We find the median perceived returns on fertilizer use to be about 4 bags, whereas the mean was about 5 bags. About 28 percent of our farmers actually used fertilizer, and we find higher perceived returns among these fertilizer users, but the difference is not statistically significant (one-sided p-value $= 0.702$).

In a similar way, we investigated the perceived returns on proper water management. Rice is grown in bunded, continuously flooded fields to ensure sufficient water and to control weeds. We find average perceived returns on proper water management to be slightly higher than perceived returns on fertilizer use. About 84 percent of farmers in our sample reported managing water according to recommended practices. Perceived returns were only 3.4 bags among those who did not manage water well, as opposed to 5.6 bags among those who did manage water well, and this difference is significant (p-value $= 0.056$).

Finally, we looked at the perceived returns on the use of good-quality seed. In particular, we asked farmers to estimate the yields they would get if they used improved rice seed obtained from a certified seed distributor, as opposed to their own recycled seed. The average estimate of returns on improved seed was about 5.8 bags per acre. About 18 percent of farmers reported using improved seed. Here too, we find that those who used improved seed perceived returns to be considerably higher than those who did not (p-value < 0.001).

Assuming farmers' perceived return on an intensification investment is too low, we would expect that improving their knowledge about the measured expected returns on inputs and technologies may increase adoption. The aim of the RI treatment was to provide information about these returns. However, we do not find significant differences in perceived returns between those who were shown the RI video and those who were not. Moreover, we find that perceptions related to the returns on the two intensification investments featured in the video (fertilizer use and water management) were consistently higher than previous studies have shown, which runs counter to the hypothesis that farmers underadopt because they perceive the benefits to be too low. However, we saw above that farmers who use fertilizer do not have higher perceived returns than those who do not. This result may indicate that the majority of farmers already have a good idea about the returns to fertilizer use, making the RI intervention less effective for fertilizer. Farmers may have learned more had the video focused on improved seed. Unfortunately, we did not provide information about the returns on improved seed in the RI video because it is not straightforward to determine seed quality.

5.2 Impact on Adoption of Technologies and Recommended Practices

Now that we have found some evidence that people learned from the videos, at least from the TI video, we look at the impact of showing agricultural information videos on the actual adoption of the technologies that are shown in the videos. We do so through looking at the difference in adoption of a particular practice at endline between those who viewed the video and those who did not, using a linear regression framework. The results are provided in Table 2. The first model shown in column (1) simply estimates the average difference in adoption rates between the treatment group and the control group and corresponds to the estimate of β in Equation 1 in the Inference section. Model (2) (shown in column 2), which controls for the matching-by-design, is the within-group (fixed-effects) estimate corresponding to the estimate of β in Equation 2 in the Inference section. Model (3) (shown in column 3) controls for the baseline value of the dependent variable in addition to the matching-group fixed effects in the second model and corresponds to the estimate of β in Equation 3. The top panel in the table reports differences between farmers who were shown the TI video and those who were not. The bottom panel reports differences between farmers who were shown the RI video and those who were not.

The first intensification technology we look at is the use of inorganic fertilizer (in general, DAP, NPK, or urea). A household is considered to have adopted the technology if it reported using any amount of inorganic fertilizer on any of its plots. Using this definition, we find that about 41 percent of our farmers adopted fertilizer use in the second rice-growing season of 2016. The first row in Table 2 shows that, on average, adoption was about 2.4 to 3.0 percent higher among households that were shown the TI video, if one does not control for baseline values (models [1] and [2], shown in columns 1 and 2, respectively). However, the differences are not statistically different from 0. When baseline data are added, the difference becomes negative, but it is again not significant. The bottom panel shows similar results for the RI video: informing a farmer about the expected returns on investment in fertilizer use does not seem to increase fertilizer adoption. Possibly, other factors may prevent farmers from adopting fertilizer, even after being made aware of its correct use and potential benefits. For instance, fertilizer may simply not be available, or households may face credit or labor constraints.

Next, we look at early transplanting. As we did for fertilizer use, we first determine early transplanting at the household level. We calculate the number of days between sowing and transplanting for each plot and then take the minimum of this number as representing the time between sowing and transplanting at the household level. We then construct an indicator that takes the value of 1 if the number of days is less than or equal to 14 days to represent the adoption status of the early transplanting practice. Doing so, we find that about 27 percent of rice farmers transplanted early in the second season of 2016. We do not find that either video had a significant impact on the proportion of households that reported adoption of the practice. This is surprising because the TI video did seem to increase awareness of early transplanting as a recommended agronomic practice. As we will argue below, the unusual weather patterns during the growing season may, to some extent, explain why we fail to find a significant effect.

The TI and RI treatments both promoted proper water management. On average, we find that in the endline, about 88 percent of households reported that they had kept water in the field during the entire rice growing season. Among the sample of farmers who did not receive the TI treatment, the proportion is about 84 percent, whereas it is 7.4 percentage points higher among those who did receive the TI treatment. Although not significant at conventional levels, this difference has a p-value of 0.110, and the coefficient

Table 2: Impact of agricultural extension information on technology adoption

	(1)	(2)	(3)
	Technical information		
Used fertilizer	0.024	0.030	-0.049
	(0.069)	(0.073)	(0.071)
Transplanted early	0.016	0.019	0.003
	(0.076)	(0.093)	(0.097)
Managed water	0.074	0.076	0.077
	(0.046)	(0.051)	(0.052)
Used nursery	0.111+	0.085	0.005
	(0.064)	(0.069)	(0.067)
	Return on investment		
Used fertilizer	0.000	-0.026	0.009
	(0.069)	(0.073)	(0.069)
Transplanted early	-0.033	-0.037	-0.039
	(0.076)	(0.093)	(0.097)
Managed water	0.030	0.012	0.010
	(0.047)	(0.051)	(0.052)
Used nursery	0.119+	0.095	0.101
	(0.064)	(0.068)	(0.065)

Source: Authors

Notes: Standard errors in parantheses.

+, *, and ** denote significance at the 10 percent, 5 percent, and 1 percent level

stays remarkably stable over the various specifications. The bottom panel shows that farmers who were shown the RI video have a higher likelihood of managing water well, but the difference is again not significant.

Finally, we look at the use of a nursery bed and transplanting, as opposed to simply broadcasting seed directly in the rice plot. Overall, 70 percent of farmers indicated that they used a nursery bed on at least one of their rice plots during the second season of 2016. This proportion is only 65 percent among farmers who did not see the TI video, but it increases to 75 percent among farmers who did get to see the TI video ($p = 0.086$). The difference is even 1 percentage point higher in the case of the RI video ($p = 0.065$). For the RI treatment in particular, the treatment effect is fairly consistent across specifications. The fact that we do find some evidence that the TI and especially the RI treatment had an effect on the use of a nursery bed but not on timely transplanting may again be related to the unusual weather during the study period and suggests that farmers postpone transplanting when there is a drought.

We also collected endline information on some practices for which we did not have baseline information. **Row planting** was practiced on only 23 percent of the plots, suggesting ample room to increase productivity through adoption of this practice. Even though row planting is promoted in both the TI and RI videos, we do not find a significant impact of viewing either of the videos on the likelihood of adopting row planting. This result may be because row planting is quite labor-intensive, which may be the binding constraint for adoption of this technology. The videos also recommend planting **2 seedlings per hill**. We find that overall, farmers reported planting on average 2.5 seedlings, and the median was 3.0 seedlings per hill. About 37 percent follow the correct practice. Also here, we do not find a significant impact of viewing either of the videos. Conversations in the field made clear that strong traditions may mean that more is needed than just showing a video once. Farmers also seem to plant more than recommended for visual reasons: some argued that when only 2 seedlings are planted, the field looks empty. Furthermore, because relatively little seed is needed to plant a given area, farmers may feel the cost of planting 3 instead of 2 seedlings is negligible. Therefore, it may be important to put more emphasis on the effect of nutrient, water, and light competition on yields. We also devote some attention in the technology video to **bund construction**. In particular, the video recommends that bunds be 20 inches high and 20 inches wide. We find in the self-reported data, however, that bunds are slightly wider on average than they are high, at 20.7 inches wide (with a median of 24.0 inches) and 19.5 inches high (with a median of 18.0). However, we do not find significant differences between farmers who were shown the TI video and those who where not. It seems that farmers measure bund dimensions in feet, and this aggregation may affect the results. The video also recommends a **planting depth** of 1.5 inches. On average, planting depth was about 1.9 inches, with a median of 2.0 inches.[15] We find no significant impact of showing this recommended practice in the technology video, but the effect goes in the right direction (using a quadratic loss function, the coefficient is significant at $p = 0.161$). We also show in the TI video that **distance between hills** needs to be about 8 inches. Most farmers reported using a spacing of 1 foot. Also here, we find no effect of showing the TI video.

5.3 Impact on Rice Production and Yields

We now investigate the effect of agricultural extension information on rice production. Even though we find little evidence that our videos affected the adoption of technologies and practices that were featured in the videos, production can be affected though other impact pathways on which no data were collected. The first row in Table 3 shows results for the total amount of rice the farmers produced in the second season of 2016, in (the logarithm of) kilograms. The various columns correspond to the different specifications, similar to those in Table 2. Of the 241 farmers for whom we have valid data on production, 39 indicated that they did not plant rice during the second season of 2016. An additional 19 reported that they had lost that season's entire harvest. Thus, because we base our analysis on the logarithm of quantity produced, our effective sample size is reduced to 183 farmers. Average production in our sample stands at just 1.1 metric tons. In general, we find production higher among farmers who were shown the TI video than among those who were not , but the difference is not statistically significant. The first row in the bottom panel shows that production is lower among farmers who were shown the RI video than among those who were not, but the difference is again not statistically significant.

Second, we look at the area that was planted in rice. On average, farmers' rice plots about 1.1 acres. The effect of our interventions on area planted

[15] We found that only 4 farmers reported 1.5 inches as their planting depth, suggesting that farmers do not use decimals.

is unclear apriori. Having been given information on available technologies and returns, farmers may choose to grow larger areas, leading to a positive impact. On the other hand, given that intensification technologies make up an important part of the videos, and some of these technologies are costly, farmers may decide to farm smaller areas, but more intensively, resulting in a negative coefficient estimate of area planted. We find no significant impact of our interventions on area of rice planted. Related to this, we look at the share of total available farmland that was used for rice cultivation. We find some evidence that the TI video reduced the area allocated to rice as a proportion of total available land. At the same time, we find no effect on the absolute area used for rice production. These findings seem to suggest that farmers increased their total area under cultivation as a result of the technology video.[16] Because the videos paid considerable attention to field preparation, farmers may have found it easier to start over and open up new fields for rice cultivation (switching to other crops in areas where rice was previously grown), such that the total area under cultivation increased but the area allocated to rice remained the same. This effect is present only for the TI treatment.

Finally, we look at the effect of the treatments on rice yields, defined as the quantity of rice (in kilograms) produced per acre. We find that in the endline, average rice yields were about 1.25 metric tons per acre, slightly lower than the 1.45 metric tons per acre reported for the eastern part of the Country in the 2008/2009 Uganda census of Agriculture Uganda Census of Agriculture 2008/09 (UBOS 2010). We do not find significant differences in yields between farmers who were shown the TI video and those who were not. Similarly, we do not find an impact of the RI video on rice yields.

5.4 Impact on Noncognitive Traits

There is increasing recognition that socioemotional skills and noncognitive personality traits such as attitudes and aspirations play an important role in explaining why some people appear to remain trapped in poverty (Ray 2006; Dalton, Ghosal, and Mani 2016). Also, in the context of agricultural technology adoption, personality characteristics such as fatalism or impatience have been linked to technology adoption (Abay, Blalock, and Berhane 2017;

[16] Indeed, in the endline, area under cultivation is on average 3.2 acres among farmers in the control group, and 3.7 acres among farmers who got to see the technology video, even though the difference is not significant, as judged by a simple t-test.

Table 3: Impact of technical knowledge on rice production

	(1)	(2)	(3)
	Technical information		
Total rice production (log[kg])	0.056	0.063	0.012
	(0.125)	(0.131)	(0.137)
Area used for rice prod. (log[acre])	0.029	0.088	-0.139
	(0.081)	(0.085)	(0.127)
Share of land used in rice prod.	-0.058	-0.075	-0.079+
	(0.044)	(0.046)	(0.046)
Rice yield (kg/acre)	-19.411	-118.092	-138.153
	(125.751)	(133.380)	(142.005)
	Return on investment		
Total rice production (log[kg])	-0.018	-0.130	-0.096
	(0.125)	(0.130)	(0.139)
Area used for rice prod. (log[acre])	0.032	-0.009	-0.049
	(0.081)	(0.085)	(0.128)
Share of land used in rice prod.	0.006	0.017	0.017
	(0.044)	(0.046)	(0.046)
Rice yield (kg/acre)	-54.890	-59.841	-69.893
	(125.707)	(132.551)	(140.810)

Source: Authors

Notes: Standard errors in parantheses.

+, *, and ** denote significance at the 10 percent, 5 percent, and 1 percent level

Van Campenhout, D'Exelle, and Lecoutere 2015). Viewing a video of a successful farmer may also affect some of these personality traits in the viewer. For instance, viewing an image of a successful farmer may make farmers more ambitious and increase their aspirations, leading them to consider an additional set of investment options (Tanguy et al. 2014). It may also affect their locus of control, by making them more aware of actions they themselves can take to increase yields. We therefore asked study participants a range of questions that aimed to capture differences in attitudes and beliefs between different treatments. We expected that the RI video in particular, with its focus on viewing rice growing as a business, would be able to affect attitudes.

We started from a set of fairly standard questions that have been used elsewhere in the literature (Kosec and Mo 2017; Bernard, Dercon, and Taffesse 2011). However, a recent study found that with such questions, acquiescence bias, whereby the respondent answers what he or she thinks the interviewer wants to hear instead of giving an honest opinion, is pervasive (Laajaj and Macours 2017). We confirmed this bias in our sample upon testing the questions in the field and made significant changes to questions to reduce this problem. In particular, we found out during pretesting that answers tended toward the extremes of the Likert scales that are standard for questions of this type. Therefore, we simply asked whether farmers agreed or not and added a third option that indicated the person did not understand the question or was not able to answer it for some reason. In addition, we often changed the wording to make the statements more moderate.[17] However, analysis of the data still shows little variability in the responses, suggesting that acquiescence bias may still be a problem.

In general, farmers who view rice growing as a business instead of as a means to feed their families are more likely to experiment with new technologies. We asked two questions to gauge the extent to which farmers saw rice growing as a business. First, we directly asked farmers whether they see rice growing as their main business. All but one of the farmers we interviewed responded that rice growing was indeed their main business.[18] Second, we asked whether the farmer wants his or her children to become rice farmers as well. About 83 percent of farmers responded affirmatively to this question.

[17] For example, instead of asking whether a farmer thinks he or she has *only* good qualities, we would ask whether the farmer thinks he or she has *mostly* good qualities.

[18] We follow our pre-analysis plan, which stated that to reduce the impact of low variability, we will not evaluate the impact of the videos on outcomes for which more than 90 percent of observations have the same value.

We do not find that having been shown the RI video has an impact on the answer to this question.

Our videos also devote considerable attention to **advance planning and time management**. We therefore included the question, "When you make plans, do you stick to them?" For this question, we allowed four options (*almost always, mostly, rarely, almost never*). We find that about 24 percent of farmers reported rarely or almost never sticking to their plans. We do not find that having been shown any of the videos led to significant differences between groups in sticking to their plans. A related question, whether farmers adhere to their goals in farming, suffered from a lack of variation, probably due to acquiescence bias, with more than 98 percent of farmers answering that they did. Farmers also claimed that they like to try out new things even if they know there is a high chance something will go wrong (94 percent).

Related to **aspirations**, we asked farmers to compare how much rice they would like to get from 1 acre with how much they currently get. The average farmer reported that he or she would like to get about 6.5 bags more per acre than what he or she currently gets. Similarly, to get an idea of what farmers thinks they are capable of, we asked them to compare how much rice they think the best farmer in the village gets from 1 acre with how much they themselves get. The average farmer thought the best farmer would be able to get about 4 bags more per acre. Neither of these differences seems to be significantly affected by our interventions. Interestingly, the number of bags the average farmer thought he or she was capable of producing is higher than the number of bags the average farmer would like to get from 1 acre, suggesting that farmers' aspirations are lower than their idea of what is achievable.

When we come to the standard statements to measure **locus of control**, the acquiescence bias leads to puzzling results. For instance, more than 98 percent of farmers agreed with the statement, "Chance determines what happens in your life," pointing toward a strong external locus of control. In addition, 84 percent of farmers agreed with the statement, "Other people such as your wife/husband, pastor, other family members, local leaders, and others determine what happens in your life." These questions attempted to capture two different types of external locus of control. We find that these proportions are lower among farmers who received the TI treatment and also among those who received the RI treatment; however, in both cases, the difference from the control group is not significant. However, when an interaction effect is added to the regression, the effect becomes significantly negative. Thus, being shown both the TI and RI videos leads to a significantly lower external locus of control. We also asked wether farmers agreed that important events (good and bad) that happen in their life were meant to happen, capturing a sense of predestination. About 75 percent of farmers agreed with this statement. We again find no difference in this proportion conditional on having seen either treatment video. A last statement asserted that poor people are poor because they do not work hard enough to improve their lives. About 81 percent of farmers agreed with this statement. There is some evidence that this proportion is higher among farmers who saw the RI video, with the coefficient on the RI treatment becoming significant if an interaction effect is included.

6 Discussion

The finding that the videos did not have much impact on agricultural technology adoption, application of recommended practices, or outcomes such as production or yields is somewhat surprising, in the light of the finding that people did learn something from the videos. For instance, we find that farmers who had viewed the TI video were more aware of the importance of timely transplanting (Figure 2), yet they did not seem to actually practice early transplanting more than others (Table 2). This result may be because farmers are (additionally) constrained by factors other than information gaps, such as land, labor, or cash. Unfortunately, the small sample size does not allow us to investigate heterogeneity in the treatment effect: comparing, for example, the relationship between exposure to a video and fertilizer adoption in a subsample of poor farmers with the same relationship among a subsample of rich farmers is likely to suffer from a lack of statistical power. Below, we provide additional explanation for the null results that are related to the design of the experiment.

First, we feel the treatments may be to blame. Rice growing is a complex activity, and it was often challenging to capture the technical details on film. For instance, bund height and width was indicated on-screen using simple animated arrows indicating measurements in decimal numbers. This approach may have been problematic; we found out when inquiring about planting depth that farmers do not use decimals (Footnote 15). The RI video in particular contains a lot of fairly complex cost-benefit calculations, which perhaps make the video no very engaging. This line of thought underlines the importance of content creation, suggesting that more research may be needed on how to frame a particular message to make it more engaging.

Second, even after testing for homogeneous effects, we may have ended up with insufficient statistical power. The second rice-growing season of 2016 was affected by an unusually strong El Nino and record-breaking high temperatures. Drought and erratic rainfall meant that many farmers delayed planting or ended up not planting at all. Almost 20 percent of farmers in the study did not plant any rice that season, citing water-related concerns, so these farmers had to be dropped from endline analyses. An additional 8 percent reported that they lost the complete crop, further reducing the number of observations in some of the specifications that use the logarithm of production or yields.[19] In addition, some of the recommended practices are conditional on other practices. For example, early transplanting, which is promoted as a key yield-enhancing practice, depends on using a nursery for rice. However, on almost 30 percent of the plots on which rice was grown, farmers reported not using a nursery bed but instead directly broadcasting the seed in the field. This phenomenon substantially reduced the sample on which we could test whether our video was effective in promoting early transplanting among rice growers.

There is some support for this second explanation in the data. Many of the effects go in the expected direction. Often, when more data can be used, we seem to be more likely to find significant effects.[20] For instance, when we model the proportion of plots where a nursery was used, we can use about 220 observations. We find that the proportion of plots on which a nursery is used is 12 percentage points higher among farmers who got to see the technology video and 10 percent higher among farmers who got to see the returns video. In both cases, the difference is significant at 10 percent. Similarly, when we use the 220 observations, we find that the technology video resulted in a 12 percent increase in the proportion of plots where rice was submerged during growth. Estimates are less convincing if we look at differences in the adoption of recommended practices such as plant spacing or plant depth, for which we can use information for only the 160 plots on

[19] The poor season is also reflected in the proportion of rice farmers who transplanted early. Compared with the baseline data, the proportion of farmers who transplanted early in the second season of 2016 drops by almost 30 percent. This result is consistent with reports from the field that many farmers delayed transplanting in that season because there was no water in the rice fields.

[20] This seems to be particularly the case for practices that do not need monetary inputs.

which a nursery was used.

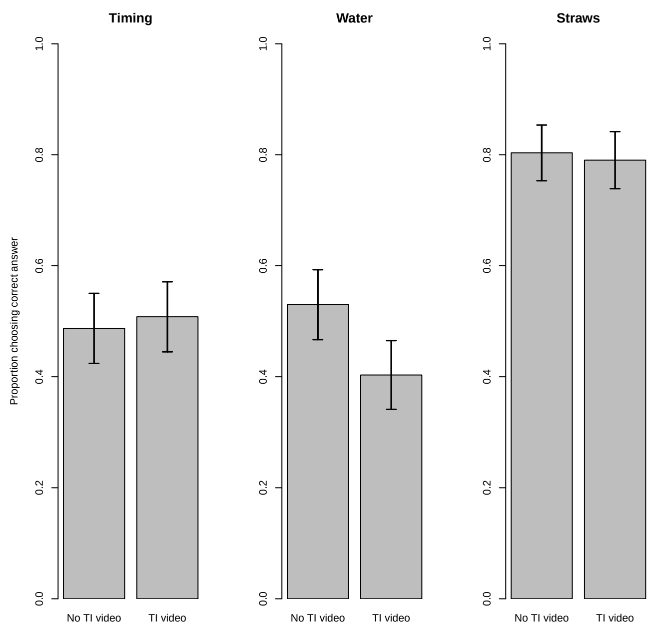
A third explanation is related to spillover effects. Our experiment takes the individual farmer as the experimental unit. Although experiments with randomization at this level have more statistical power than experiments that randomize at higher levels, they are also more susceptible to spillover effects: Suppose a farmer allocated to the control group resides close to a farmer allocated to the treatment group. When these two farmers interact and the treated farmer conveys some of the information he or she learned from the video to the farmer in the control group, the farmer in the control group may also benefit from the treatment, which may also improve outcomes for the farmer in the control group. Thus, the difference in outcomes between the treated and control farmer, through which the effectiveness of the intervention is judged, will become smaller due to these spillover effects, and the experiment will be compromised.

There is some support for spillover effects. During the endline survey, we repeated the exact questions that had been asked immediately after the treatment, in order to investigate whether farmers had learned something from the intervention. The results are presented in Figure 3, which is the endline equivalent of Figure 2. The first pair of bars, in particular, is consistent with spillover effects from the technology video. Although the subgroup that did not get to see the technology video did significantly worse in answering the question on timely transplanting immediately after having been shown the placebo video (Figure 2), this group seems to have caught up by endline. For the question related to what to do with straws, the difference in knowledge between those who got to see the TI video and those who did not also seems to have vanished by endline. Spillovers are also consistent with the significant increase in the use of fertilizer observed between baseline and endline. Again, additional research is needed to learn about spillover effects. For example, researchers could survey rice farmers in a different parish sufficiently far away from parishes included in the study to rule out spillovers. These farmers results on the same multiple-choice questions could be compares with those of control farmers who were included in the study.

7 Conclusion

Limited knowledge about the existence, use, and profitability of certain modern inputs and recommended agronomic practices are thought to be one of the

Figure 3: Technical knowledge at endline



Source: Authors.
Note: TI = technical information.

main reasons why intensification investments are not more widely adopted among smallholders in developing countries. This may be particularly true for rice farmers because information may be especially important in farming activities that are complex or require precise implementation. To overcome these information inefficiencies, various actors have started providing information. For instance, some governments have started to provide agricultural extension services on a large scale.

We assessed the importance of agricultural extension information through a small field experiment among rice farmers in Uganda. Using a factorial design, we differentiated between two different types of information deficiency. First, we looked at information gaps at a technical level, where we assumed that farmers lack information about the existence and use of modern inputs or recommended practices. To test the importance of this type of information, we developed an intervention that provide farmers with technical information about the existence and use of some modern inputs and recommended practices, such as early transplanting and inorganic fertilizer use. Second, we looked at knowledge gaps related to the return on investing in intensification inputs and technologies. The hypothesis here was that farmers lack the necessary information to assess the profitability or return on investment of modern inputs or recommended farming methods. To test the importance of this information gap, we developed an intervention that explained the basics of investment decision making and pointed out expected returns on different intensification investments. Both interventions took the form of simple videos in which a model farmer provided the information. These videos were then shown to individual farmers.

We find some evidence that providing technical information through short agricultural extension videos raised awareness about the existence and use of modern inputs and recommended practices. In particular, we find that farmers who saw a video that recommended transplanting after 14 days were more likely to select this option as the recommended practice from a list of alternatives than were farmers who did not see the video. We also find that viewing a video about modern inputs and best practices increased farmers' knowledge about an intensification practice not explicitly featured in the video, suggesting that farmers may actively engage in abstraction and use knowledge gained in one context in a different context. On the other hand, though we do find that, on average, farmers who use a certain input or practice also perceive higher benefits from that input or practice than farmers who do not use it, we do not find that pointing out returns on certain inputs or practices in a short video message changes perceived returns.

The impact of our intervention is not sustained when we turn to actual adoption of the practices shown in the video. For instance, we find no effect of either of the videos on fertilizer use, early transplanting, or water management. We also find little impact on eventual outcomes, such as rice quantities produced, area planted, and rice yields. We do find some evidence that showing a video that promotes rice growing as a business and points out the additional yields that can be obtained through intensification investments makes farmers feel they are more in control of their lives. However, the few significant coefficients we do find are not entirely convincing: most likely, these effects would also disappear if we took into account that the likelihood of false positives increases when multiple hypotheses are tested. That said, we do provide some evidence that our failure to find any significant effect may be related to a lack of power due to the small sample size, spillover effects, or both.

This study shows that the use of ICT to provide agricultural extension information is feasible, but that behavioral changes and impact on production may be more modest than expected. Future studies should keep the latter point in mind and aim for sample sizes that are sensitive to more modest changes in adoption, especially if the study promotes technologies with which farmers are already somewhat familiar. One particularly promising area of future research is related to spillover effects: interventions at the individual level targeted at randomly (exogenously) selected farmers within a community may be more effective in disseminating information than those that provide information to (endogenously formed) farmer groups.

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